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**Land Use Mapping with Evidential Fusion of Polarimetric Synthetic Aperture  
Radar and Hyperspectral Imagery**

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# **Land Use Mapping using Evidential Fusion of Polarimetric Synthetic Aperture Radar and Hyperspectral Imagery<sup>1</sup>**

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## **Abstract**

As part of the Earth Observation Application Development Program (EOADP) program sponsored by the Canada Space Agency, Lockheed Martin Canada has developed the Intelligent Data Fusion System (IDFS) for evidential fusion of features extracted from polarimetric SAR and Hyperspectral imagery. This paper presents the use of IDFS for land use mapping.

IDFS is made of three modules. The polarimetric SAR module contains polarimetric classifiers (Cloude decomposition, polarization response parameters), textural classifiers (GLCM, backscattering coefficient) that provide hypotheses about the likelihood that some object of interest may be present in the scene based on textural and scattering properties of the analysed surface. The Hyperspectral module contains the Iterative Error Analysis endmembers selection technique proposed by the Canada Center for Remote Sensing to provide a set of pixel-based hypotheses reflecting the likelihood that some typical material may be present in the scene based on the spectral properties of the analysed surface. Hypotheses provided by each module represent an incomplete, inaccurate and imprecise description of the reality. The data fusion module combines PolSAR and HSI hypotheses using the evidence theory proposed by Dempster-Shafer.

This paper presents an overview of the current functionality of IDFS. Results of evidential fusion are shown for land use mapping. The data-sets acquired over Indian-Head (Saskatchewan) with an airborne C-Band CV-580 PolSAR sensor and HSI Probe-1 imagery were provided by the Canada Center for Remote Sensing.

## **1. Introduction**

The project “Intelligent Data Fusion System (IDFS) for airborne/spaceborne SAR and Hyperspectral Data Analysis” has been awarded by the Canadian Space Agency to Lockheed Martin Canada as part of the Earth Observation Application Development Program (EOADP). The objective of the project is to demonstrate the synergy between Synthetic Aperture Radar

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(SAR) and Hyperspectral imagery for land use mapping. The type of soil, vegetation, crops, man-made structures, the crop condition are expected to be more precisely and accurately described when fusing features extracted from both imageries.

Figure 1 shows the high level diagram of IDFS proposed in [Jouan A. & al, 2001]. Three separate modules can be recognized, one for each imagery and an additional one to handle the evidential fusion. Each image module contains software to extract features from the imagery. These features are used to build generic hypotheses. The performance of the features extractors is used to weight each hypothesis with a level of confidence. Since each of these measures is incomplete and inaccurate, it is expected that the combination of them will contribute to generate more confidence. These hypotheses are combined using Dempster-Shafer evidence theory that is the most appropriate combination scheme for this type of data.

The fused hypotheses may be thresholded to build a resulting map (lower right of the diagram) or may be left untouched to be combined with another set of declarations obtained at a later time or from another sensor. G.I.S. themes can also be used in the decision process to confirm or not the result of the fusion.

IDFS is written in C/C++ using Lockheed Martin Canada CORTEX architecture.

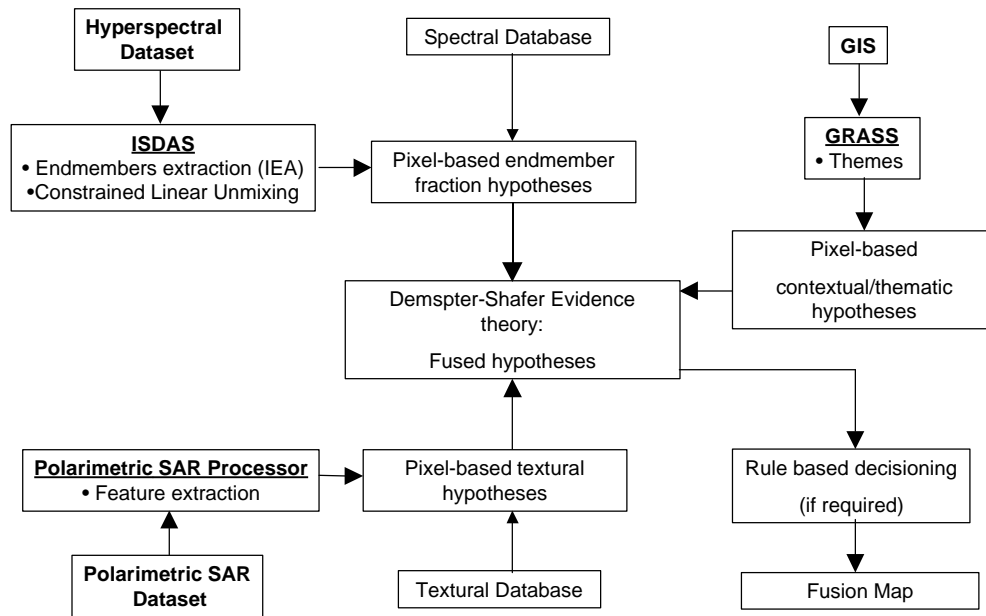


Figure 1 – IDFS High Level Diagram

## 2. IDFS Image Modules

The IDFS polarimetric SAR processor contains a textural classifier (using GLCM features on each plarimetric channel) and a polarimetric classifier (co-polarized and cross-polarized responses, Cloude's  $\alpha$ -H representation). Details can be found in [Jouan A. & al, 2001].

### 2.1 Textural Features and Polarimetric Classifiers

Table 1 summarizes the main characteristics of each of the selected feature extractors and classifiers.

Name of Agent	Data	Description
<b>BackscatterCrossSection</b>	Partial/ Fully Polarimetric	Scattering classification from fuzzy membership functions
<b>PolarizationResponse</b>	Fully Polarimetric	Parameters from polarization response
<b>H-A-<math>\alpha</math> Classifier</b>	Fully Polarimetric	Unsupervised Scattering classification from Coherence Matrix
<b>Grey-Level Cooccurrence Matrix</b>	Partial/Fully Polarimetric	Parameters from the GLCM

**Table 1 Textural Features and Polarimetric Classifiers for the IDFS PolSAR Module**

The IDFS will automatically trigger the computations that are relevant to the input data (single or multiple polarizations). As an example, the backscatter cross-sections and the GLCM parameters will be computed on single polarization channels and/or fully polarimetric data, while the other classifiers will only work on fully polarimetric data.

## ***2.2 The IDFS Hyperspectral Image Processor***

Several algorithms have been proposed to extract spectral end-members from Hyperspectral data. As an example the n-FINDR using a simplex method in the hyperspectral space [Winter M.E., 1999], DAFE [Landgrebe D. and Jimenez L., 1999] [Landgrebe D. and Tadjudin S., 2000] or more recently the Independent Component Analysis [Bayliss J., 1997].

The IDFS Hyperspectral Image Processor will use the output of the Iterative Error Analysis (IEA) end-members selection which is part of the Imaging Spectrometer Data Analysis System (ISDAS) software package developed by the Canada Center for Remote Sensing (CCRS) and MacDonald Dettwiler and Associates [Szeredi T. & al.] [Lefebvre J.H. & al.] [Staenz K. & al., 2000] [Staenz K. & al., 1998] [Deguise J.C. & al., 1999]. ISDAS features visualization tools for displaying imaging spectrometer data together with data input, output, pre-processing, information extraction modules (such as the IEA) and a spectral library. Since the IDFS project is focused on exploiting the synergy between polarimetric SAR and HI data, it seems logical to use CCRS's expertise in Hyperspectral Image processing to get faster to the focal point of the study. Each endmember generated by the IEA will be used to define a specific spectral declaration. A spectral endmembers fraction declaration will be built for each pixel of the scene by attaching to each spectral declaration (endmember) a mass (or belief) whose value is given by the corresponding endmember fraction.

When for a given pixel a subset of endmember fractions are below a given threshold (to be defined during the tuning of the method), it can be said that the belief associated to the spectral contribution of the corresponding endmembers to the pixel spectrum is low. As a consequence,

the summation of the corresponding endmember fractions can be attributed to the ignorance defined as the union of all the spectral declarations ( all endmembers).

Such pixel-based spectral declaration can then be used in Dempster- Shafer evidence theory to combine various data sets (as an example a temporal sequence of the same scene) unmixed with the same set of endmembers or to combine pixel-based spectral declaration to other identity declarations obtained by processing data sets provided by other sensors.

### 3. Evidential Fusion of PolSAR and HI Features

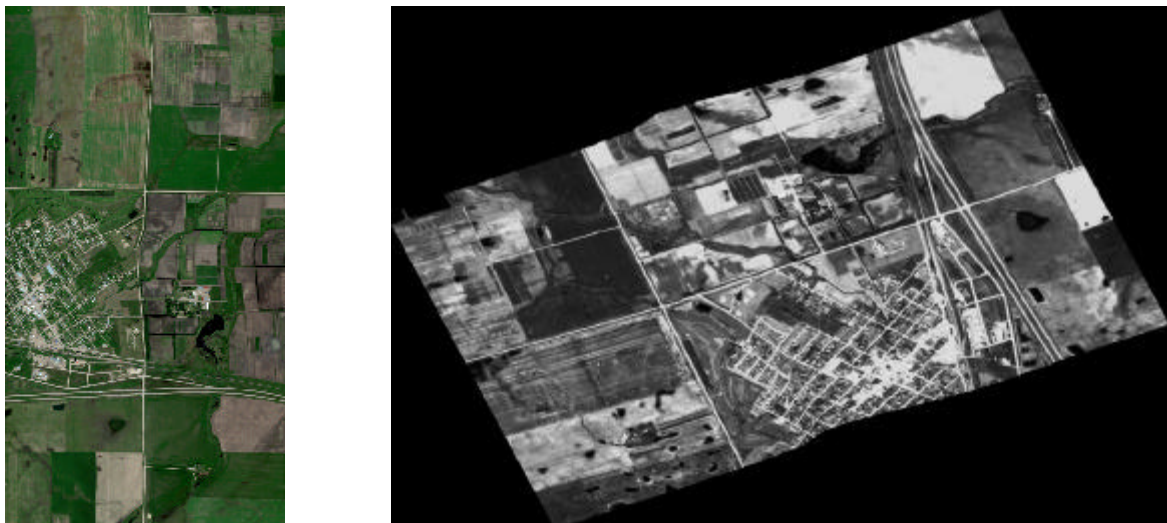
#### 3.1 PolSAR and HSI Datasets

In order to evaluate the synergy between polarimetric SAR and HI data for land used mapping, IDFS has been designed to extract various features from both imagery. The evidential fusion of these features is expected to provide a more complete and accurate description of the observed scene.

Figure 2 shows the area of interest from the Probe-1 hyperspectral datacube (left) and its roll-corrected and coregistered version (right).

Figure 3 shows the amplitude of the four C-band polarimetric channels for a selected area around the city of Indian-Head. The resolution of the PolSAR is 4m in slant range and 43cm in azimuth.

As it can be seen on Figure 2 and Figure 3, geometric distortions due to the movement of the aircraft (CV-580) during the acquisition are not totally compensated. HSI data still shows large deformations when compared to the PolSAR data.



**Figure 2. Line 2 Indian Head (SK) 2000 (left :HI, right: roll-corrected and co-registered with PolSAR)**



HH resampled



HV resampled



VH resampled



VV resampled

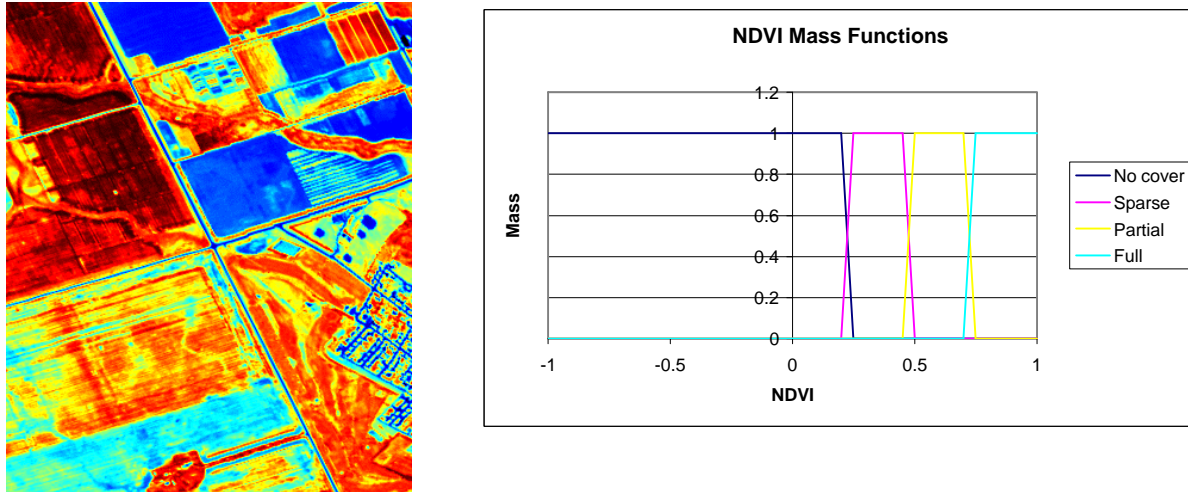
Figure 3 PolSAR scene extracted from the IndianHead (SK) dataset.

### 3.2 HSI Generic Propositions and their associated mass functions

The spectral end-members generated by the IEA are extremely important for the classification and identification of objects according to their spectral properties. Spectral end-members with the use of ground truth data or appropriate spectral libraries can be used to create **specific** identity declarations. If such a priori data is not available, other spectral features can be used to create more **generic** propositions. Their use for fusion requires the definition of mass functions that represent the level of confidence associated with the corresponding feature. In the next sections, some of the selected spectral features are listed as long as with their associated mass functions.

#### 3.2.1 The Normalized Difference Vegetation Index (NDVI)

The NDVI is sensitive to the presence of green vegetation. However it tends to over-estimate the percentage of vegetative cover at the beginning of the growth season and under-estimate it at the end of the growth cycle.

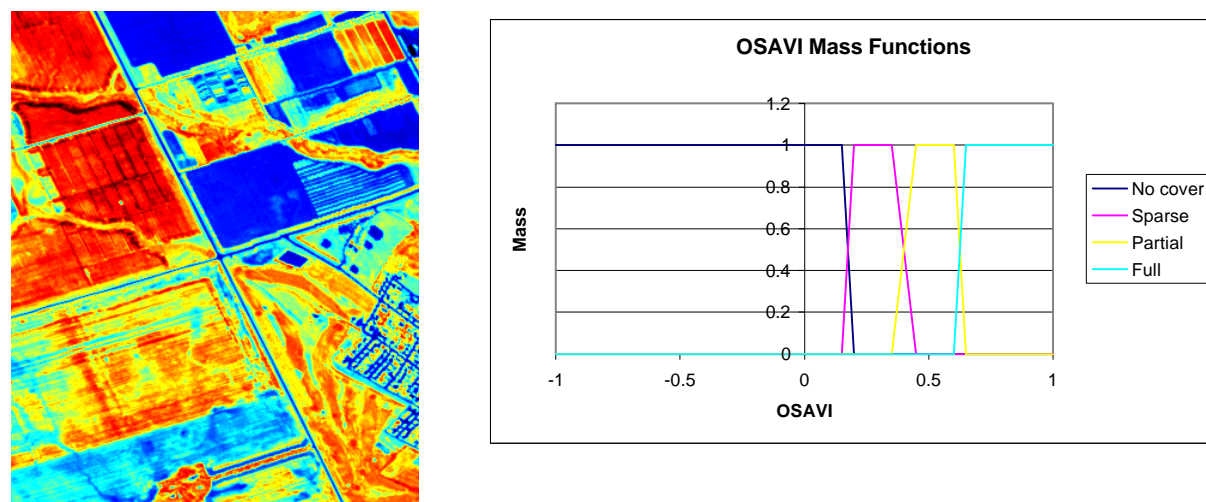


**Figure 4 Map of the Normalized Difference Vegetation Index (left) and Mass Functions (right).**

This index will give support to the following proposition: Bare Surface (water, soil and man-made object), Vegetation and to proposition related to percentage of vegetation cover ( no cover, spare cover, partial cover and full cover). Figure 4 shows the mass functions associated with these propositions.

### 3.2.2 *The Optimized Soil Adjusted Vegetation Index (OSAVI)*

The OSAVI has been incorporated in the system to evaluate vegetation density and condition. Reports in the literature show that OSAVI gives excellent results over agricultural crops. Its combination with the TCARI (described later) permits the evaluation of leaf chlorophyll content (which is useful to evaluate crop and vegetation condition). Figure 5 show the OSAVI map computed over the area of interest.



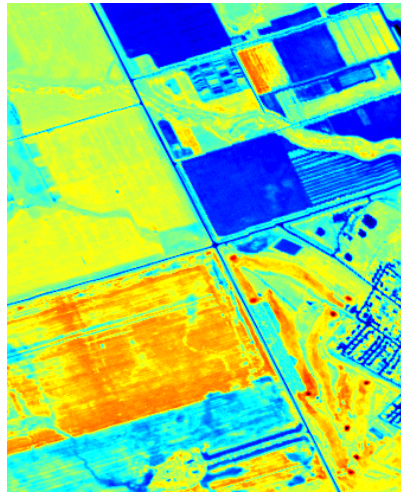
**Figure 5 Map of the Optimized Soil-Adjusted Vegetation Index (left) and Mass Functions (right).**



The following graph shows the associated mass functions and their supported propositions (which are the same than for the NDVI).

### **3.2.3 *The Transformed Chlorophyll Absorption Ratio Index (TCARI)***

The spectral index TCARI is used in remote sensing to estimate the absorbed photosynthetically active radiation. It will be used in combination with the spectral index OSAVI to give a quantitative estimation of leaf chlorophyll content. Figure 6 shows the TCARI map computed over the selected region of interest.

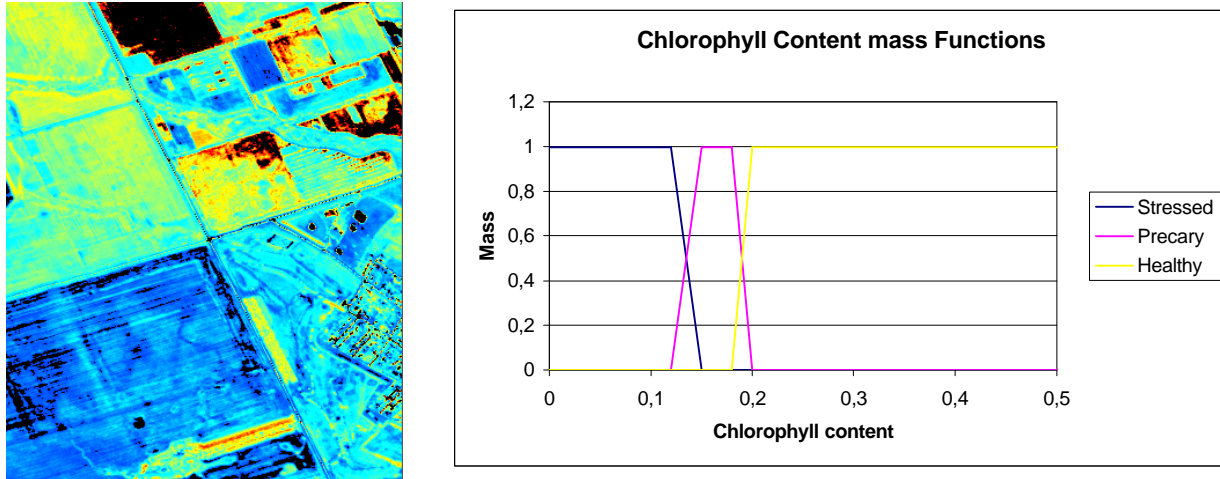


**Figure 6. Map of the Transformed Chlorophyll Absorption Ratio Index.**

We have not defined any mass function for this spectral index since it will no be used alone for evidential fusion. Only its combination with the OSAVI (see next section) will be used for fusion.

### **3.2.4 *Ratio TCARI/OSAVI for Chlorophyll Content Estimation***

[Haboudane and al., 2001] have shown that the ratio TCARI/OSAVI can be used to make accurate predictions of crop chlorophyll content from airborne hyperspectral imagery. The TCARI/OSAVI will be used in IDFS to estimate the condition of the vegetation. However, the proposed prediction model is valid over a certain range of the ratio TCARI/OSAVI. This is why the chlorophyll content peaks appear where they shouldn't, the ratio being near the limit of the valid range of prediction. Figure 7 shows the chlorophyll content of vegetation over the selected region of interest.

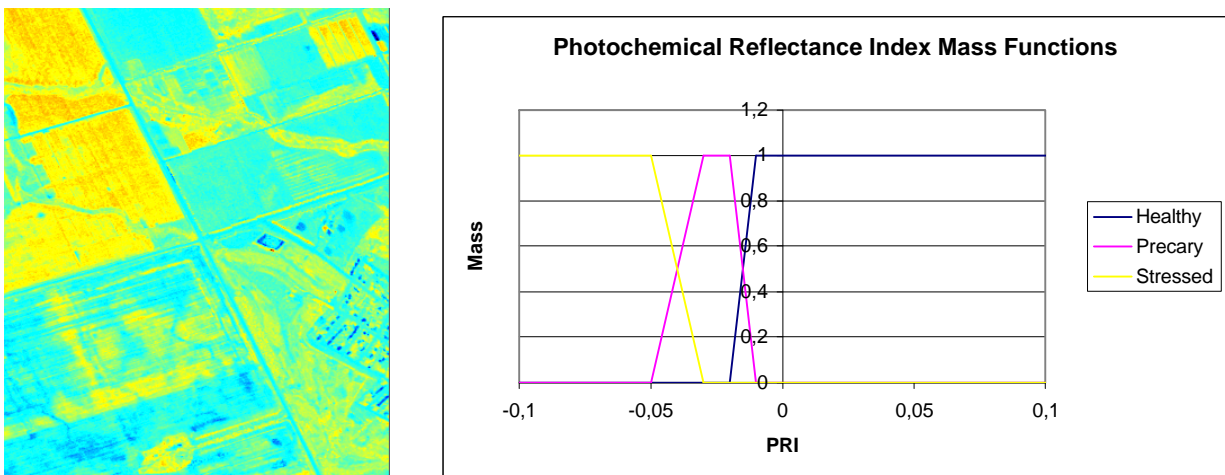


**Figure 7. Map of the ratio of the spectral indices TCARI/OSAVI (left) and mass functions (right) associated to generic propositions (Stressed, Precary, Healthy).**

The ratio TCARI/OSAVI will give support to generic propositions related to the vegetation condition: Stressed, Precary, Healthy. Figure 7 shows the mass functions and their associated propositions.

### 3.2.5 The Photochemical Reflectance Index (PRI)

The PRI is an index of xanthophylls activity and photosynthetic performance. If this index is high, it indicates that the leaf of the canopy are in good shape and then that the plant is in good health. Figure 8 shows the PRI map computed over the selected region of interest.

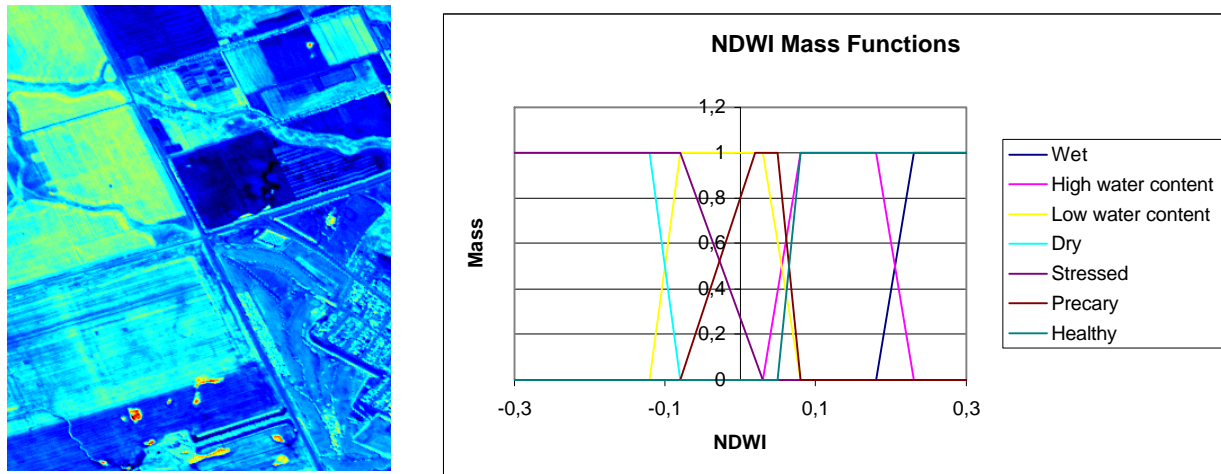


**Figure 8. Map of the Photochemical Reflectance Index (left) and Mass Functions associated to generic propositions [Healthy, Precary, Stressed] (right).**

The spectral index PRI will be used to support some generic propositions related to vegetation condition. Figure 8 represents the mass functions with their associated propositions.

### 3.2.6 The Normalized Difference Water Index (NDWI)

The NDWI is related to the leaf water content. This information will be fused with the one from WBI to derive a qualitative water content evaluation. Since the water content of the leaf can reflect its condition, this index will also provide support for some generic propositions related to vegetation condition. Figure 9 shows the NDWI map computed over the selected region of interest.

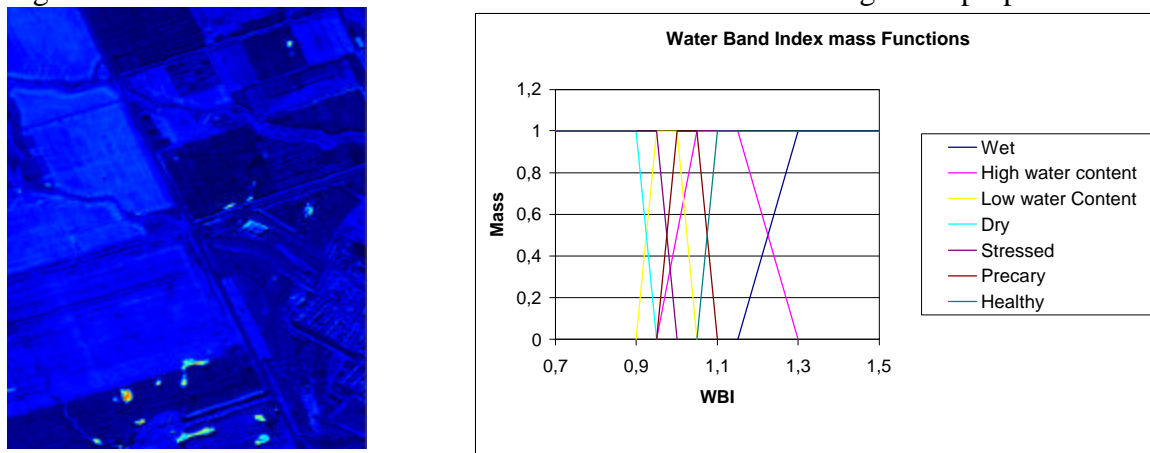


**Figure 9. Map of the Normalized Water Difference Index (left) and Mass Functions associated to generic propositions (Wet, High Water Content, Low Water Content, Dry, Stressed, Precary, Healthy).**

Figure 9 represents the mass functions and the associated propositions for the NDWI.

### 3.2.7 The Water Band Index (WBI)

Studies have demonstrated the strong relationship of the WBI and the canopy water content. This water index will then be used in combination with the NDWI to estimate qualitative water content for the vegetation canopy and to support generic propositions related to the vegetation condition. Figure 10 shows the WBI and the mass functions associated to the generic propositions.

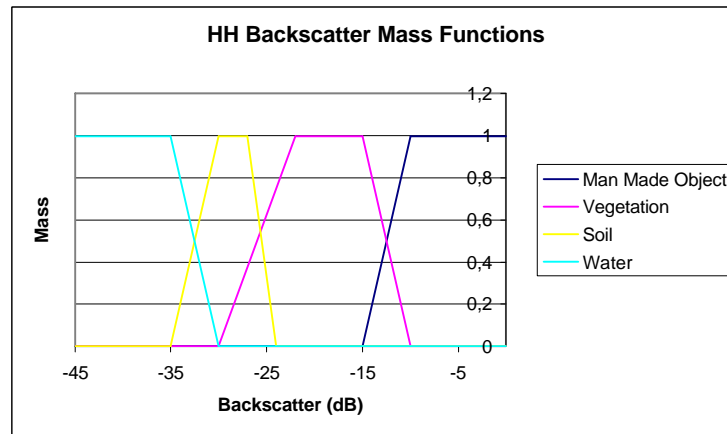


**Figure 10. Map of the Water Band Index (left) and Mass Functions associated to generic propositions [Wet, High Water Content, Low Water Content, Dry, Stressed, Precary, Healthy] (right).**

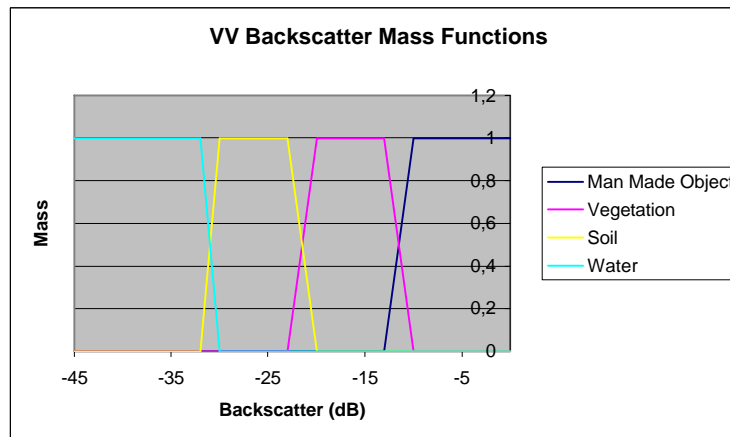
### 3.3 Generic Propositions from PolSAR Features

#### 3.3.1 Radar Backscatter

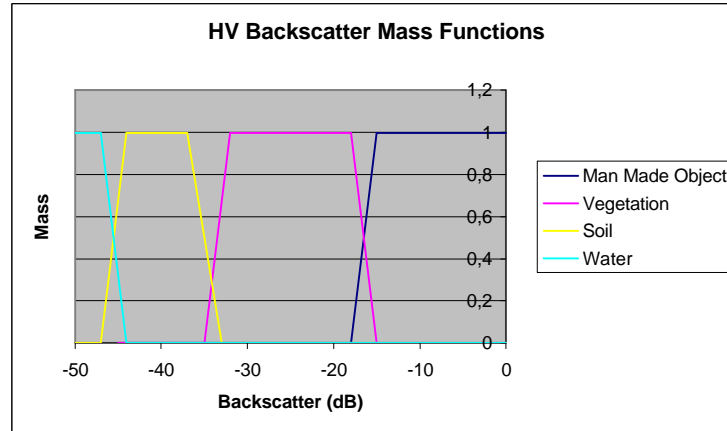
Radar backscatter will be used in IDFS to refine the generic proposition “bare surface” since the backscatter can easily discriminate against man-made object, water and bare soils. Figure 11, Figure 12 and Figure 13 represent the mass functions with the associated propositions for the radar backscatter.



**Figure 11. Mass Functions associated to generic propositions [Man Made Object, Vegetation, Soil, Water] created from the radar backscatter on HH polarimetric channel.**



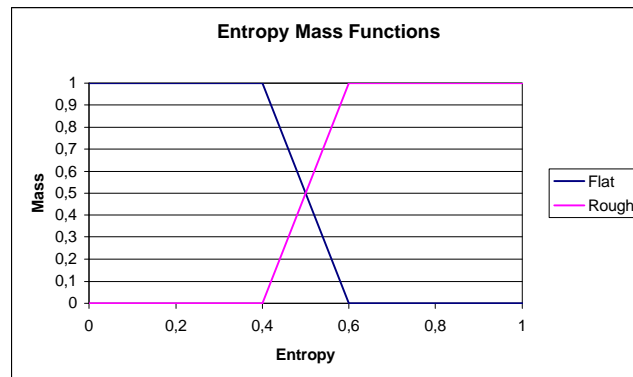
**Figure 12. Mass Functions associated to generic propositions [Man Made Object, Vegetation, Soil, Water] created from the radar backscatter on VV polarimetric channel.**



**Figure 13. Mass Functions associated to generic propositions [Man Made Object, Vegetation, Soil, Water] created from the radar backscatter on HV polarimetric channel.**

### 3.3.2 Cloude's Polarimetric Decomposition

The entropy derived from the eigenvalues of the coherency matrix will be used to create the generic propositions related to surface roughness (flat or rough). The higher the entropy, the higher the probability that the surface is rough. Figure 14 represents the mass functions associated to the generic propositions generated from the polarimetric entropy (Cloude's decomposition).



**Figure 14. Mass Functions associated to generic propositions [Flat, Rough] created from the entropy calculated on polarimetric channels.**

## 4. Results

The following sections give typical examples of the improvement brought to the description of the ground cover by the evidential fusion of features provided by PolSAR and HSI imagery. This is presented in a hierarchical manner, from a general to a more precise description of the scene.

### 4.1 Discrimination between Bare Surface – Vegetated Cover

A first description of the scene can be obtained using the hyperspectral vegetation indexes. They will provide initial declarations about the type of surface we are looking at (“bare surface” vs “vegetated cover”).

## 4.2 Identification of Bare Surface Subtype

Then, the “bare surface” proposition can be further refined in three subtypes, namely “man-made object”, “water” and “bare soils” using PolSAR features.

The mass functions associated to the backscatter feature of the three polarimetric channels described in section 3.3.1 are used for evidential fusion. Figure 15 show the display of the land cover description when PolSAR backscatter information is fused with the hyperspectral vegetation indices.

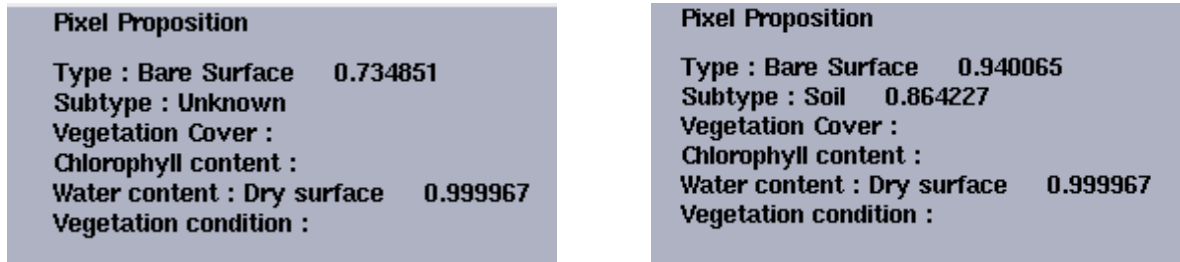


Figure 15. Description of the land cover using generic propositions produced by spectral vegetation indices (left); refinement after fusion with propositions produced by polarimetric backscatter (right).

## 4.3 Determination of Vegetation Ground Cover (Density)

The initial declaration provided by the vegetation indices can also be used to determine the density of the vegetation cover. Both, NDVI and the OSAVI can be used to achieve this goal. Their associated mass functions and generic propositions have been described in sections 3.2.1 and 3.2.2.

An example of characterization of the vegetation ground cover using evidential fusion is illustrated in the next sections.

## 4.4 Determination of Vegetation Condition

Several parameters are used to evaluate the condition of the vegetation. First, there is the chlorophyll content that has been computed using the ratio TCARI/OSAVI as proposed by Haboudane and al. Then, the PRI, which is related to the photochemical activity, provide another useful information for the evaluation of the vegetation’s condition. The leaf water content will also be used in the fusion since it supports vegetation condition proposition. Figure 16, Figure 17

are examples of IDFS output. Each provides a description of the condition as well as the cover percentage for vegetated area.

Pixel Proposition	
Type : Vegetation	0.999947
Subtype :	
Vegetation Cover : Full	0.999947
Chlorophyll content : 28.7438 ug/cm2	
Water content : High content	0.998747
Vegetation condition : Healthy	0.999966

Pixel Proposition	
Type : Vegetation	0.999999
Subtype :	
Vegetation Cover : Partial	0.761309
Chlorophyll content : 14.9117 ug/cm2	
Water content : Low content	0.854009
Vegetation condition : Healthy	0.98822

Figure 16. Full cover, healthy vegetation (left); partial cover, healthy vegetation (right).

Pixel Proposition	
Type : Vegetation	0.999947
Subtype :	
Vegetation Cover : Partial	0.953344
Chlorophyll content : 12.7345 ug/cm2	
Water content : Low content	0.998747
Vegetation condition : Precary	0.999966

Pixel Proposition	
Type : Vegetation	0.960948
Subtype :	
Vegetation Cover : Partial	0.550859
Chlorophyll content : 13.2604 ug/cm2	
Water content : Dry surface	0.617674
Vegetation condition : Stressed	0.520543

Figure 17. Partial cover, precary condition (left), partial cover, stressed vegetation (right).

#### 4.5 Determination of Surface Water Content

Two water related spectral indices can be used to evaluate the surface water content, the WBI and NDWI. Figure 18 and Figure 19 show typical generic propositions and their associated beliefs generated by evidential fusion of water indices for the water content estimation.

Pixel Proposition	
Type : Bare Surface	0.939634
Subtype : Soil	0.864227
Vegetation Cover :	
Chlorophyll content :	
Water content : Dry surface	0.999967
Vegetation condition :	

Pixel Proposition	
Type : Vegetation	0.999999
Subtype :	
Vegetation Cover : Full	0.999995
Chlorophyll content : 19.6823 ug/cm2	
Water content : High content	0.998747
Vegetation condition : Healthy	0.999966

Figure 18. Dry surface condition (left), high water content (right)



Pixel Proposition	
Type : Vegetation	0.962373
Subtype :	
Vegetation Cover : Very sparse	0.813596
Chlorophyll content : 20.9068 ug/cm2	
Water content : Low content	0.974434
Vegetation condition : Precary	0.836238

Figure 19. Low water content

## 5. Conclusion

This paper presents the first results obtained for evidential fusion of PolSAR and HIS features with IDFS. Examples have been shown that evidential fusion of PolSAR and HSI features improves the description of the land cover by providing insight in the percentage of vegetated cover, its condition and water content.

Ground truth data will be used to build the specific propositions that can be created from the spectral end-members extraction. Additional HSI features are going to be fused such as the spectral uniformity index grouping pixels characterized by the same set of end-members and in the same order.

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